"We hereby declare that we have read this thesis and in our opinion this thesis is sufficient in terms of scope and quality for the award of the degree of Doctor of Philosophy (*Mechanical Engineering*)"

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BAHAGIAN A – Pengesahan Kerjasama*

Adalah disahkan bahawa projek penyelidikan tesis ini telah dilaksanakan melalui kerjasama antara ________________________ dengan ________________________

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BLADE FAULT DIAGNOSIS USING ARTIFICIAL INTELLIGENCE TECHNIQUE

NGUI WAI KENG

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Mechanical Engineering)

Faculty of Mechanical Engineering
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NOVEMBER 2016

I declare that this thesis entitled "*Blade Fault Diagnosis Using Artificial Intelligence Technique*" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ABSTRACT

Blade fault diagnosis is conventionally based on interpretation of vibration spectrum and wavelet map. These methods are however found to be difficult and subjective as it requires visual interpretation of chart and wavelet color map. To overcome this problem, important features for blade fault diagnosis in a multi row of rotor blade system was selected to develop a novel blade fault diagnosis method based on artificial intelligence techniques to reduce subjective interpretation. Three artificial neural network models were developed to detect blade fault, classify the type of blade fault, and locate the blade fault location. An experimental study was conducted to simulate different types of blade faults involving blade rubbing, loss of blade part, and twisted blade. Vibration signals for all blade fault conditions were measured with a sampling rate of 5 kHz under steady-state conditions at a constant rotating speed. Continuous wavelet transform was used to analyse the vibration signals and its results were used subsequently for feature extraction. Statistical features were extracted from the continuous wavelet coefficients of the rotor operating frequency and its corresponding blade passing frequencies. The extracted statistical features were grouped into three different feature sets. In addition, two new feature sets were proposed: blade statistical curve area and blade statistical summation. The effectiveness of the five different feature sets for blade fault detection, classification, and localisation was investigated. Classification results showed that the statistical features extracted from the operating frequency to be more effective for blade fault detection, classification, and localisation than the statistical features from blade passing frequencies. Feature sets of blade statistical curve area was found to be more effective for blade fault classification, while feature sets of blade statistical summation were more effective for blade fault localisation. The application of feature selection using genetic algorithm showed good accuracy performance with fewer features achieved. The neural network developed for blade fault detection, classification, and localisation achieved accuracy of 100%, 98.15% and 83.47% respectively. With the developed blade fault diagnosis methods, manual interpretation solely dependent on knowledge and the experience of individuals can be reduced. The novel methods can therefore be used as an alternative method for blade fault diagnosis.

ABSTRAK

Diagnosis kecacatan bilah adalah lazimnya berdasarkan interpretasi ke atas spektrum getaran dan peta gelombang kecil. Kaedah ini akan tetapi didapati sukar dan subjektif kerana ia memerlukan interpretasi secara visual ke atas carta dan peta berwarna gelombang kecil. Untuk mengatasi masalah ini, sifat-sifat penting untuk diagnosis kecacatan bilah pada satu sistem rotor bilah yang berbilang baris telah dipilih untuk membangunkan satu kaedah diagnosis kecacatan bilah novel berdasarkan kepada teknik-teknik kecerdasan buatan bagi mengurangkan interpretasi subjektif. Tiga tiruan rangkaian neural model telah dibangunkan bagi mengesan kecacatan bilah, mengelas jenis kecacatan bilah, dan mencari lokasi kecacatan bilah. Satu eksperimen telah dijalankan untuk mensimulasikan beberapa jenis kecacatan bilah yang berbeza termasuk geseran bilah, kehilangan sebahagian bilah, dan bilah terpiuh. Isyarat getaran untuk semua keadaan kecacatan bilah telah diukur pada keadaan mantap dengan kadar pensampelan 5 kHz pada kelajuan tetap. Transformasi gelombang kecil berterusan telah digunakan untuk menganalisa isyarat getaran dan keputusan seterusnya digunakan bagi pengekstrakan sifat. Sifat-sifat statistik telah diekstrak dari pekali gelombang kecil berterusan pada frekuensi operasi pemutar dan frekuensi berlalu bilah yang sepadan. Sifat-sifat statistik yang telah diekstrak telah dikumpulkan kepada tiga set sifat yang berasingan. Di samping itu, dua set sifat baru telah dicadangkan iaitu *blade statistical curve area* dan *blade statistical summation*. Keberkesanan lima set sifat yang berbeza untuk pengesanan kecacatan bilah, pengelasan, dan penyetempatan telah dikaji. Keputusan klasifikasi menunjukkan bahawa sifat-sifat statistik diekstrak dari frekuensi operasi lebih berkesan bagi pengesanan kecacatan bilah, pengelasan, dan penyetempatan berbanding sifat-sifat statistik dari frekuensi berlalu bilah. Set sifat *blade statistical curve area* adalah didapati lebih berkesan bagi pengelasan kecacatan bilah, manakala set sifat *blade statistical summation* adalah lebih berkesan bagi penyetempatan kecacatan bilah. Aplikasi pemilihan sifat menggunakan algoritma genetik menunjukkan prestasi ketepatan yang baik dengan sifat-sifat yang lebih sedikit dicapai. Rangkaian neural yang dibangunkan bagi pengesanan kecacatan bilah, pengelasan, dan penyetempatan masing-masing mencapai ketepatan 100%, 98.15% dan 83.47%. Dengan kaedah diagnosis kecacatan bilah yang dibangunkan, interpretasi secara manual yang semata-matanya bergantung kepada pengetahuan dan pengalaman individu dapat dikurangkan. Dengan ini, kaedah novel ini boleh digunakan sebagai kaedah alternatif bagi diagnosis kecacatan bilah.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
BPF	-	Blade passing frequency
BPF_1_CF_X	-	Crest factor from the first BPF in the horizontal direction
BPF_1_CF_Y	-	Crest factor from the first BPF in the vertical direction
BPF_1_CM_X	-	Central moment from the first BPF in the horizontal direction
BPF_1_CM_Y	-	Central moment from the first BPF in the vertical direction
BPF_1_E_X	-	Energy from the first BPF in the horizontal direction
BPF_1_E_Y	-	Energy from the first BPF in the vertical direction
BPF_1_ESE_X	-	Energy to Shanon entropy ratio from the first BPF in the horizontal direction
BPF_1_ESE_Y	-	Energy to Shanon entropy ratio from the first BPF in the vertical direction
BPF_1_KUR_X	-	Kurtosis from the first BPF in the horizontal direction
BPF_1_KUR_Y	-	Kurtosis from the first BPF in the vertical direction
BPF_1_M_X	-	Mean from the first BPF in the horizontal direction
BPF_1_M_Y	-	Mean from the first BPF in the vertical direction
BPF_1_RMS_X	-	RMS from the first BPF in the horizontal direction
BPF_1_RMS_Y	-	RMS from the first BPF in the vertical direction
BPF_1_SE_X	-	Shanon entropy from the first BPF in the horizontal direction

BPF_1_SE_Y - Shanon entropy from the first BPF in the vertical direction

BPF_1_SK_X - Skewness from the first BPF in the horizontal direction

BPF_1_SK_Y - Skewness from the first BPF in the vertical direction

BPF_1_STD_X - Standard deviation from the first BPF in the horizontal direction

BPF_1_STD_Y - Standard deviation from the first BPF in the vertical direction

BPF_1_V_X - Variance from the first BPF in the horizontal direction

BPF_1_V_Y - Variance from the first BPF in the vertical direction

BPF_2_CF_X - Crest factor from the second BPF in the horizontal direction

BPF_2_CF_Y - Crest factor from the second BPF in the vertical direction

BPF_2_CM_X - Central moment from the second BPF in the horizontal direction

BPF_2_CM_Y - Central moment from the second BPF in the vertical direction

BPF_2_E_X - Energy from the second BPF in the horizontal direction

BPF_2_E_Y - Energy from the second BPF in the vertical direction

BPF_2_ESE_X - Energy to Shanon entropy ratio from the second BPF in the horizontal direction

BPF_2_ESE_Y - Energy to Shanon entropy ratio from the second BPF in the vertical direction

BPF_2_KUR_X - Kurtosis from the second BPF in the horizontal direction

BPF_2_KUR_Y - Kurtosis from the second BPF in the vertical direction

BPF_2_M_X - Mean from the second BPF in the horizontal direction

BPF_2_M_Y	-	Mean from the second BPF in the vertical direction
BPF_2_RMS_X	-	RMS from the second BPF in the horizontal direction
BPF_2_RMS_Y	-	RMS from the second BPF in the vertical direction
BPF_2_SE_X	-	Shanon entropy from the second BPF in the horizontal direction
BPF_2_SE_Y	-	Shanon entropy from the second BPF in the vertical direction
BPF_2_SK_X	-	Skewness from the second BPF in the horizontal direction
BPF_2_SK_Y	-	Skewness from the second BPF in the vertical direction
BPF_2_STD_X	-	Standard deviation from the second BPF in the horizontal direction
BPF_2_STD_Y	-	Standard deviation from the second BPF in the vertical direction
BPF_2_V_X	-	Variance from the second BPF in the horizontal direction
BPF_2_V_Y	-	Variance from the second BPF in the vertical direction
BPF_3_CF_X	-	Crest factor from the third BPF in the horizontal direction
BPF_3_CF_Y	-	Crest factor from the third BPF in the vertical direction
BPF_3_CM_X	-	Central moment from the third BPF in the horizontal direction
BPF_3_CM_Y	-	Central moment from the third BPF in the vertical direction
BPF_3_E_X	-	Energy from the third BPF in the horizontal direction
BPF_3_E_Y	-	Energy from the third BPF in the vertical direction
BPF_3_ESE_X		Energy to Shanon entropy ratio from the third BPF in the horizontal direction

BPF_3_ESE_Y	-	Energy to Shanon entropy ratio from the third BPF in the vertical direction
BPF_3_KUR_X		Kurtosis from the third BPF in the horizontal direction
BPF_3_KUR_Y	-	Kurtosis from the third BPF in the vertical direction
BPF_3_M_X	-	Mean from the third BPF in the horizontal direction
BPF_3_M_Y	-	Mean from the third BPF in the vertical direction
BPF_3_RMS_X	-	RMS from the third BPF in the horizontal direction
BPF_3_RMS_Y	-	RMS from the third BPF in the vertical direction
BPF_3_SE_X	-	Shanon entropy from the third BPF in the horizontal direction
BPF_3_SE_Y	-	Shanon entropy from the third BPF in the vertical direction
BPF_3_SK_X	-	Skewness from the third BPF in the horizontal direction
BPF_3_SK_Y	-	Skewness from the third BPF in the vertical direction
BPF_3_STD_X	-	Standard deviation from the third BPF in the horizontal direction
BPF_3_STD_Y	-	Standard deviation from the third BPF in the vertical direction
BPF_3_V_X	-	Variance from the third BPF in the horizontal direction
BPF_3_V_Y	-	Variance from the third BPF in the vertical direction
BSCA	-	Blade statistical curve area
BSCA_CF_X	-	Crest factor from the BSCA in the horizontal direction
BSCA_CF_Y	-	Crest factor from the BSCA in the vertical direction
BSCA_CM_X	-	Central moment from the BSCA in the horizontal direction
BSCA_CM_Y	-	Central moment from the BSCA in the vertical direction
BSCA_E_X	-	Energy from the BSCA in the horizontal direction
BSCA_E_Y	-	Energy from the BSCA in the vertical direction

BSCA_ESE_X	-	Energy to Shanon entropy ratio from the BSCA in the horizontal direction
BSCA_ESE_Y	-	Energy to Shanon entropy ratio from the BSCA in the vertical direction
BSCA_KUR_X	-	Kurtosis from the BSCA in the horizontal direction
BSCA_KUR_Y	-	Kurtosis from the BSCA in the vertical direction
BSCA_M_X	-	Mean from the BSCA in the horizontal direction
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BSCA_SE_Y	-	Shanon entropy from the BSCA in the vertical direction
BSCA_SK_X	-	Skewness from the BSCA in the horizontal direction
BSCA_SK_Y	-	Skewness from the BSCA in the vertical direction
BSCA_STD_X	-	Standard deviation from the BSCA in the horizontal direction
BSCA_STD_Y	-	Standard deviation from the BSCA in the vertical direction
BSCA_V_X	-	Variance from the BSCA in the horizontal direction
BSCA_V_Y	-	Variance from the BSCA in the vertical direction
BSS	-	Blade statistical summation
BSS_CF_X	-	Crest factor from the BSS in the horizontal direction
BSS_CF_Y	-	Crest factor from the BSS in the vertical direction
BSS_CM_X	-	Central moment from the BSS in the horizontal direction
BSS_CM_Y	-	Central moment from the BSS in the vertical direction
BSS_E_X	-	Energy from the BSS in the horizontal direction
BSS_E_Y	-	Energy from the BSS in the vertical direction
BSS_ESE_X	-	Energy to Shanon entropy ratio from the BSS in the horizontal direction

BSS_ESE_Y	-	Energy to Shanon entropy ratio from the BSS in the vertical direction
BSS_KUR_X	-	Kurtosis from the BSS in the horizontal direction
BSS_KUR_Y	-	Kurtosis from the BSS in the vertical direction
BSS_M_X	-	Mean from the BSS in the horizontal direction
BSS_M_Y	-	Mean from the BSS in the vertical direction
BSS_RMS_X	-	RMS from the BSS in the horizontal direction
BSS_RMS_Y	-	RMS from the BSS in the vertical direction
BSS_SE_X	-	Shanon entropy from the BSS in the horizontal direction
BSS_SE_Y	-	Shanon entropy from the BSS in the vertical direction
BSS_SK_X	-	Skewness from the BSS in the horizontal direction
BSS_SK_Y	-	Skewness from the BSS in the vertical direction
BSS_STD_X	-	Standard deviation from the BSS in the horizontal direction
BSS_STD_Y	-	Standard deviation from the BSS in the vertical direction
BSS_V_X	-	Variance from the BSS in the horizontal direction
BSS_V_Y	-	Variance from the BSS in the vertical direction
CF	-	Crest factor
CFD	-	Computational Fluid Dynamics
CM	-	Central moment
CWT	-	Continuous Wavelet Transform
E	-	Energy
EMD	-	Empirical Mode Decomposition
EPRI	-	Electric Power Research Institute
ESE	-	Energy to Shanon entropy ratio
FFT	-	Fast Fourier Transform
GA	-	Genetic Algorithm
KUR	-	Kurtosis
LDA	-	Linear Discriminant Analysis
LLE	-	Locally Linear Embedding

M	-	Mean
MLP	-	Multi-Layer Perceptron
NFS_A1	-	Feature set from the blade statistical curve area
NFS_A2	-	Feature set from the blade statistical summation
OF_CF_X	-	Crest factor from the operating frequency in the horizontal direction
OF_CF_Y	-	Crest factor from the operating frequency in the vertical direction
OF_CM_X	-	Central moment from the operating frequency in the horizontal direction
OF_CM_Y	-	Central moment from the operating frequency in the vertical direction
OF_E_X	-	Energy from the operating frequency in the horizontal direction
OF_E_Y	-	Energy from the operating frequency in the vertical direction
OF_ESE_X	-	Energy to Shanon entropy ratio from the operating frequency in the horizontal direction
OF_ESE_Y	-	Energy to Shanon entropy ratio from the operating frequency in the vertical direction
OF_KUR_X	-	Kurtosis from the operating frequency in the horizontal direction
OF_KUR_Y	-	Kurtosis from the operating frequency in the vertical direction
OF_M_X	-	Mean from the operating frequency in the horizontal direction
OF_M_Y	-	Mean from the operating frequency in the vertical direction
OF_RMS_X	-	RMS from the operating frequency in the horizontal direction
OF_RMS_Y	-	RMS from the operating frequency in the vertical direction

OF_SE_X	-	Shanon entropy from the operating frequency in the horizontal direction
OF_SE_Y	-	Shanon entropy from the operating frequency in the vertical direction
OF_SK_X	-	Skewness from the operating frequency in the horizontal direction
OF_SK_Y	-	Skewness from the operating frequency in the vertical direction
OF_STD_X	-	Standard deviation from the operating frequency in the horizontal direction
OF_STD_Y	-	Standard deviation from the operating frequency in the vertical direction
OF_V_X	-	Variance from the operating frequency in the horizontal direction
OF_V_Y	-	Variance from the operating frequency in the vertical direction
PCA	-	Principle Component Analysis
PNN	-	Probabilistic Neural Network
PSVM	-	Proximal Support Vector Machines
RBF	-	Radial Basis Function
RMS	-	Root mean square
SE	-	Shanon entropy
SFS_A1	-	Feature set from the operating frequency
SFS_A2	-	Feature set from the blade passing frequencies
SFS_A3	-	Feature set from the operating frequency and blade passing frequencies
SK	-	Skewness
SOM	-	Self-Organizing Maps
STA	-	Synchronised Time Averaging
STD	-	Standard deviation
SVM	-	Support Vector Machine
V	-	Variance
WPT	-	Wavelet Packet Transform

LIST OF APPENDICES

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